Machine Learning & Data Mining Lecture 3

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Outline

- Multivariate Regression Model Building
- Polynomial Regression Model
- Support Vector Regression (SVR) Model



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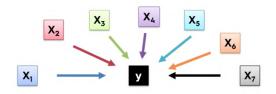


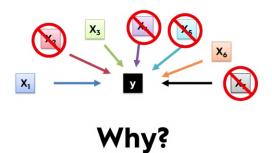
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- Multivariate Regression Model Building
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2)





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5 methods of building models:

1. All-in

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- 2. Backward Elimination

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Stepwise Regression

"All-in" - cases:



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Prior knowledge; OR



"All-in" - cases:

- · Prior knowledge; OR
- You have to; OR



"All-in" - cases:

- Prior knowledge; OR
- · You have to; OR
- Preparing for Backward Elimination



Backward Elimination



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STEP 1: Select a significance level to stay in the model (e.g. SL = 0.05)



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FIN: Your Model Is Ready

Forward Selection



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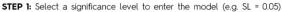


STEP 2: Fit all simple regression models $y \sim x_n$ Select the one with the lowest P-value



STEP 3: Keep this variable and fit all possible models with one extra predictor added to the one(s) you already have

Forward Selection





STEP 2: Fit all simple regression models $y \sim x_n$ Select the one with the lowest P-value

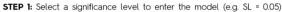


STEP 3: Keep this variable and fit all possible models with one extra predictor added to the one(s) you already have



STEP 4: Consider the predictor with the lowest P-value. If P < SL, go to STEP 3, otherwise go to FIN

Forward Selection





STEP 2: Fit all simple regression models $y \sim x_n$ Select the one with the lowest P-value



STEP 3: Keep this variable and fit all possible models with one extra predictor added to the one(s) you already have



STEP 4: Consider the predictor with the <u>lowest</u> P-value. If P < SL, go to STEP 3, otherwise go to FIN

Forward Selection

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STEP 2: Fit all simple regression models $\mathbf{y} \sim \mathbf{x}_n$ Select the one with the lowest P-value



STEP 3: Keep this variable and fit all possible models with one extra predictor added to the one(s) you already have



STEP 4: Consider the predictor with the lowest P-value. If P



go to STEP 3, otherwise go to FIN



FIN: Keep the previous model

Bidirectional Elimination



Bidirectional Elimination

STEP 1: Select a significance level to enter and to stay in the model e.g.: SLENTER = 0.05, SLSTAY = 0.05



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STEP 1: Select a significance level to enter and to stay in the model e.g.: SLENTER = 0.05, SLSTAY = 0.05





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STEP 3: Perform ALL steps of Backward Elimination (old variables must have P < SLSTAY to stay)

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STEP 2: Perform the next step of Forward Selection (new variables must have: P < SLENTER to enter)



STEP 3: Perform ALL steps of Backward Elimination (old variables must have P < SLSTAY to stay)



STEP 4: No new variables can enter and no old variables can exit



FIN: Your Model Is Ready

All Possible Models



All Possible Models

STEP 1: Select a criterion of goodness of fit (e.g. Akaike criterion)

Video on Akaike Information Criterion (AIC): https://www.youtube.com/watch?v=YkD7ydzp9_E



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STEP 2: Construct All Possible Regression Models: 2N-1 total combinations

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Example: 10 columns means 1,023 models

5 methods of building models:

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Polynomial Regression Model

Regressions

$$y=b_0+b_1x_1$$

Regressions

Simple Linear Regression

$$y=b_0+b_1x_1$$

Multiple Linear Regression

$$y = b_0 + b_1 x_1 + b_2 x_2 + ... + b_n x_n$$

Regressions

Simple Linear Regression

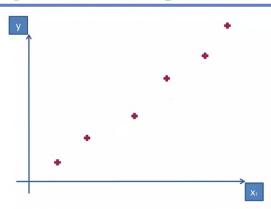
$$y=b_0+b_1x_1$$

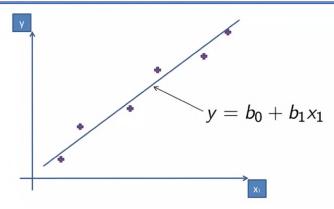
Multiple Linear Regression

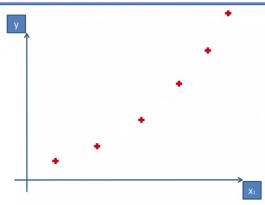
$$y = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n$$

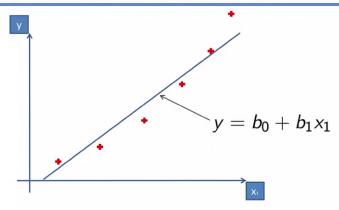
Polynomial Linear Regression

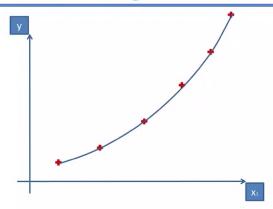
$$y = b_0 + b_1 x_1 + b_2 x_1^2 + \dots + b_n x_1^n$$

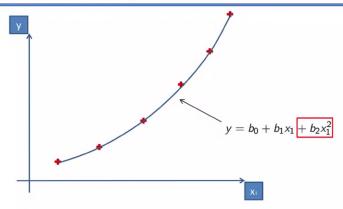










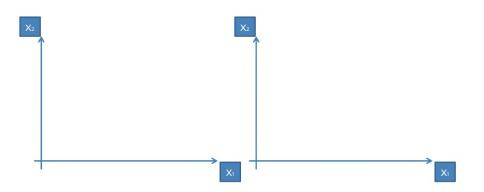


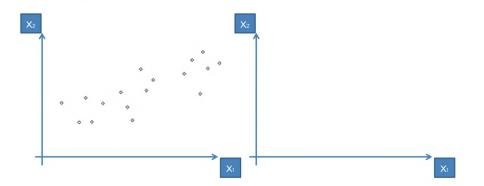
One Question: Why "Linear"?

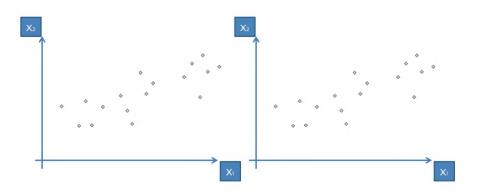
Polynomial Linear Regression

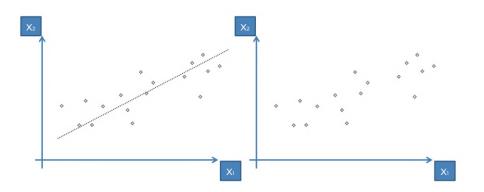
$$y = b_0 + b_1 x_1 + b_2 x_1^2 + ... + b_n x_1^n$$

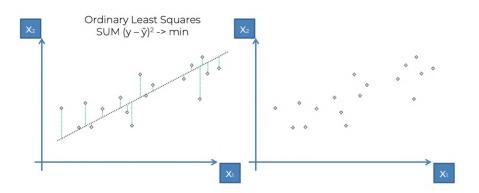
SVR Model

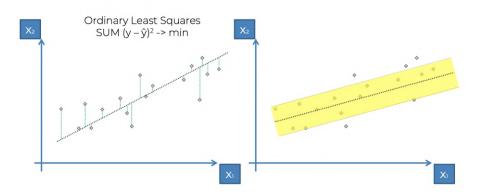


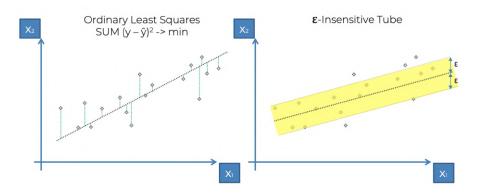


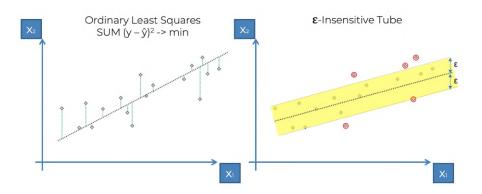


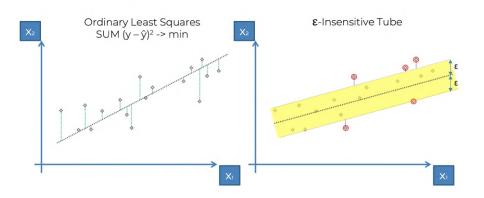


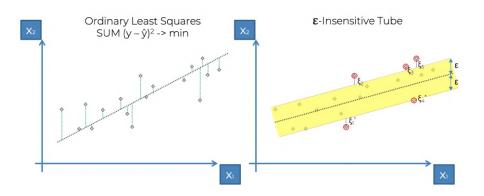


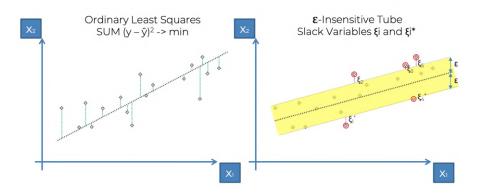


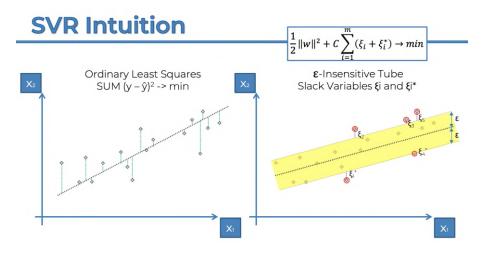


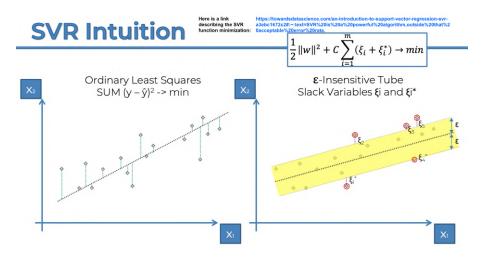


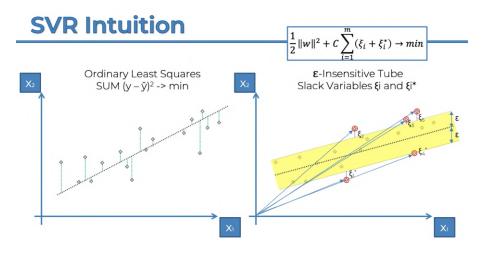








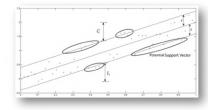




Additional Reading:

Chapter 4 – Support Vector Regression (from: Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers)

By Mariette Awad & Rahul Khanna (2015)



Link:

https://core.ac.uk/download/pdf/81523322.pdf

Let's get Started!

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